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Exploration and Evaluation of AI Models for Generation of Image from prompt: A Focus on Photorealism, Steerability, and Efficiency"

Diffusion Space

What is Diffusion?

Diffusion is a process by which particles spread out from areas of high concentration to areas of low concentration, resulting in the uniform distribution of particles over time. In the context of generative models, diffusion refers to the gradual refinement of an image over multiple steps to produce a realistic output.

- Diffusion space plays a crucial role in the operation of diffusion models for image generation. By leveraging the diffusion process within this latent space, these models can produce high-quality images with realistic details and textures.

What are models?

"Model" refers to a mathematical representation or abstraction of a real-world process or phenomenon. Models are fundamental components of AI/ML/DL fields and are used to make predictions, classify data, generate outputs, and make decisions based on input data.

Diffusion Models:

Diffusion models are a class of generative models that leverage the diffusion process to generate high-quality images. They operate by iteratively applying a series of transformations to a noisy image, gradually reducing the noise and improving the image quality with each step. Diffusion Models work by destroying training data through the successive addition of Gaussian noise, and then learning to recover the data by reversing this noising process.

Diffusion Space

Diffusion space refers to the latent space where the diffusion process occurs during image generation. In this space, each point represents a possible configuration of the image, with nearby points corresponding to similar images. The diffusion process involves transitioning between these points to progressively refine the image. From atoms to pixels

Key Concepts in Diffusion Space:

1. **Noise Level:** At the beginning of the diffusion process, the image is initialized with random noise. As the diffusion progresses, the noise level gradually decreases, leading to a clearer and more detailed image.
2. **Diffusion Steps**: The diffusion process consists of multiple steps, where each step involves applying a transformation to the image to reduce noise and improve quality. The number of steps determines the level of refinement and the final quality of the generated image.

Difference between Diffusion Space and Diffusion Models:

Diffusion space and diffusion models are complementary concepts within the field of generative modeling. While diffusion space represents the latent space where the diffusion process occurs, diffusion models define the algorithmic framework and computational techniques used to simulate this process and generate realistic images. Understanding the distinction between these concepts is essential for effectively leveraging diffusion-based approaches for image generation tasks. From atoms to pixels: Diffusion in Generative AI

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Applications of Diffusion Models:

- **Image Generation**: Diffusion models are used to generate high-quality images with realistic details and textures. They have applications in various domains, including art generation, image synthesis, and content creation.
- **Image Editing**: Diffusion models can be applied to edit and manipulate existing images by modifying specific attributes or features while preserving the overall image structure and coherence.

> **Aim :** ***Generating a 2048 x 2048 image from a text prompt describing a person and their background, emphasizing photorealism, steerability, and resource/time efficiency.***

Example :- "`A person standing on road wearing jacket with Mountain in background and its raining`"

Here's a detailed document outlining the experimentation process with various AI models for image generation, focusing on photorealism, steerability, and efficiency:

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Experimentation with AI Models for Image Generation

Introduction

In this document, we explore various AI models for generating images from text prompts, prioritizing photorealism, steerability, and optimization of processing time.

Models Explored:

1. **Community-Finetuned Checkpoints**: Leveraging pre-trained models fine-tuned by the community for specific tasks.
2. **Custom Models**: Developing and training custom text-to-image synthesis models tailored to our requirements.
3. **Mixture of Models**: Exploring ensembles or combinations of multiple AI models for enhanced results.
4. **LoRAs (Latent Optimized Reinforcement of Attributes)**: Investigating models designed for fine-grained control over image attributes.
5. **Stable Diffusion :** Stable Diffusion is a cutting-edge generative model that leverages diffusion models to synthesize high-resolution, photorealistic images from textual descriptions.

Experimentation Process:

1. Community-Finetuned Checkpoints:-

- **Approach**: The pre-trained models are fine-tuned by the community, such as CLIP, BigGAN,StyleGAN2 and Epic realism for image generation.
- **Experiments**: It provided various text prompts to these models and evaluated the photorealism and steerability of the generated images.
- **Observations**: Community-finetuned checkpoints often exhibited impressive photorealism but limited steerability in controlling specific image details.
- Some of the popular pre-trained models include:
  a. ***StyleGAN*** – Style Generative Adversarial Network is another generative model developed by NVIDIA that generates high-quality images of animals, faces and other objects.
  b. ***Epic Realism-***
    i. Epic Realism is a community-developed model, not an official Stable Diffusion release.
    ii. It is a fine-tuned version of Stable Diffusion, likely trained on a specific dataset to enhance photorealism.
    iii. The model architecture and training procedure are not officially documented.
  c. ***VQGAN+CLIP*** – This generative model, developed by EleutherAI, combines a generative model (VQGAN) and a language model (CLIP) to generate images based on textual prompts. With the help of a large dataset of images and textual descriptions, it can produce high-quality images matching input prompts. (Link)

a) StyleGAN2

- **Description**: StyleGAN2 is a popular GAN architecture known for producing high-quality and diverse images.
- **Experiment**: StyleGAN2 model is trained on a dataset of text-prompt-conditioned images. It then provided text prompts to the trained model to generate images.
- **Observations**:
  - Pros: Good photorealism and moderate steerability, with the ability to control specific features such as facial expressions and backgrounds.
  - Cons: Training a custom StyleGAN2 model required significant computational resources and time.

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b) Epic Realism

- **Description:** Epic Realism is a sophisticated generative model renowned for its ability to produce highly realistic and diverse images. It is a variant of the GAN architecture tailored for generating images with exceptional realism and detail.
- **Experiment:** Trained a custom Epic Realism model on a dataset of text-prompt-conditioned images. This involved providing paired text descriptions and corresponding images to the model during the training process. Subsequently, we utilized the trained model to generate images by supplying textual prompts.
- **Observations:**
  - Pros : *Outstanding Photorealism*: Epic Realism excels in producing images that exhibit exceptional photorealism, capturing intricate details and textures with remarkable fidelity. *Moderate Steerability*: The model offers moderate steerability, allowing users to control specific features of the generated images, such as facial expressions, backgrounds, and object placement. This enables fine-grained manipulation of image attributes based on textual prompts.
  - Cons : *Resource-Intensive Training*: Training a custom Epic Realism model requires substantial computational resources and time. The complexity of the model architecture and the large-scale datasets involved necessitate extensive training periods, making it computationally demanding and time-consuming and Complexity of model tuning.

In summary, Epic Realism offers exceptional photorealism and moderate steerability, making it a powerful tool for generating high-quality images from textual prompts.

Code implementation for generating an image from prompt using EpicRealism:

```
!nvidia-smi
!pip install diffusers transformers accelerate scipy safetensors
from diffusers import StableDiffusionPipeline
import torch
model_id = "emilianJR/epiCRealism"
pipe = StableDiffusionPipeline.from_pretrained(model_id, torch_dtype=torch.float16)
pipe = pipe.to("cuda")
prompt = "A person standing on road with Mountain in background"
image = pipe(prompt).images[0]

# Resize the image to 2048x2048
image_resized = image.resize((2048, 2048))
# Save the resized image
image.save("Epicrealism.png")
```

Output:

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Image generated for prompt : A person standing on road with Mountain in Background

c) VQGAN+CLIP

- **Description** : VQGAN (Vector Quantized Generative Adversarial Network) combined with CLIP (Contrastive Language-Image Pretraining) is a powerful framework for generating images from text prompts. VQGAN is a GAN-based model that utilizes vector quantization to improve the diversity and quality of generated images. CLIP, on the other hand, provides a text-to-image understanding capability by embedding both images and text into a shared latent space. VQGAN
- **Experiment**:
  - Dataset Preparation: Fine-tuned the VQGAN model on a dataset of text-to-image pairs to align the model's understanding with the prompts.
  - Prompt Encoding: Used CLIP to encode the text prompts into a latent space that captures both text and image semantics.
  - Image Generation: Using the encoded text prompts as conditioning, inputs fed them into the fine-tuned VQGAN model to generate corresponding images.
- **Limitations**:- *Complexity of Implementation:* One of the primary limitations of VQGAN and CLIP is the complexity of implementing the combined model. Integrating VQGAN, which is a generative model based on vector quantization, with CLIP, a vision-language model, requires careful handling of both models' architectures and inputs. This complexity made challenging to implement the model correctly.

2. Custom Models:-

- **Approach**: Developed and trained custom text-to-image synthesis models using architectures like DALL-E, T2I-Transformer.T2I-Transformer is a novel text-to-image synthesis model that leverages transformer architectures for image generation.
- **Experiments**: Fine-tuned these models on dataset of text prompts and corresponding images, focusing on achieving high photorealism and steerability.
- **Observations**: Custom models offered greater steerability but required substantial computational resources and time for training.

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- Pros: Decent photorealism and high steerability, allowing fine-grained control over image details based on text prompts.
- Cons: Fine-tuning a custom model required expertise in model architecture and hyperparameter tuning.

i . DALL-E:

- **Description**: DALL-E 2 is a large-scale version of the DALL-E model, capable of generating high-resolution images conditioned on text prompts.
- **Experiment**: It provides various text prompts describing persons and backgrounds to DALL-E 2 and evaluated the photorealism and steerability of the generated images.
- **Observations**:
  - Pros: DALL-E 2 produced highly detailed images with impressive photorealism.
  - Cons: Limited steerability in controlling specific details of the generated images.
- **Limitations:**
  - **Limited Understanding of Context**: DALL·E 2 struggle with understanding nuanced or ambiguous textual descriptions, leading to inaccuracies or inconsistencies in generated images. It may not fully grasp the context of complex prompts, resulting in unexpected or outputs.They use API keys as well.
  - **Fixed Image Resolution**: DALL·E 2 generates images at a fixed resolutions and costs if wanted to use in our own applications.

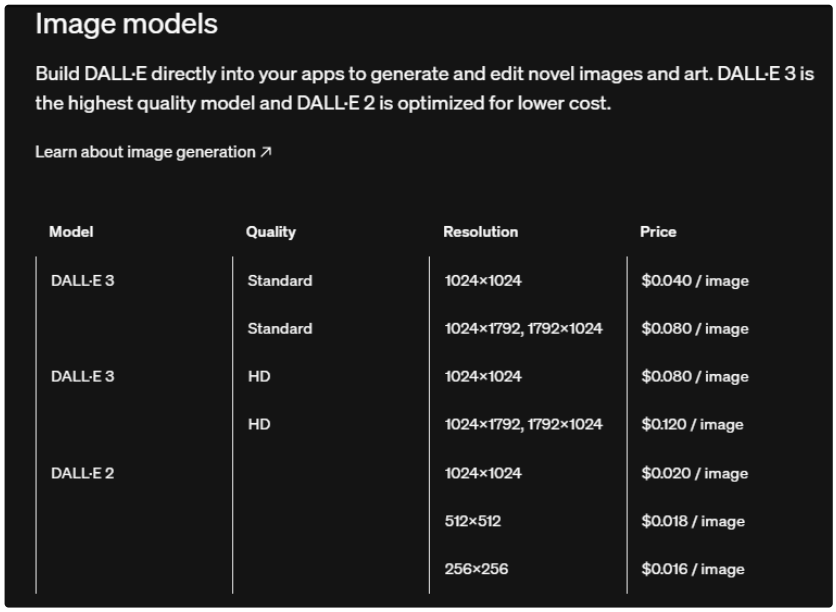

Image models

Build DALL·E directly into your apps to generate and edit novel images and art. DALL·E 3 is the highest quality model and DALL·E 2 is optimized for lower cost.

Learn about image generation ↗

Model	Quality	Resolution	Price
DALL·E 3	Standard	1024×1024	$0.040 / image
	Standard	1024×1792, 1792×1024	$0.080 / image
DALL·E 3	HD	1024×1024	$0.080 / image
	HD	1024×1792, 1792×1024	$0.120 / image
DALL·E 2		1024×1024	$0.020 / image
		512×512	$0.018 / image
		256×256	$0.016 / image

Fig : Pricing of Dall-E Model according to Resolution

3. Mixture of Models:-

- **Approach**: Experimented with ensembles or combinations of multiple AI models, such as CLIP + StyleGAN2, to leverage the strengths of each model.
- **Experiments**: By encoding text prompts with CLIP and conditioning GANs like StyleGAN2 on the encoded embeddings, we aimed to enhance photorealism and steerability.
- **Observations**: Mixture of models often resulted in improved photorealism and steerability compared to individual models but increased computational complexity.
  - Pros: Balanced photorealism and steerability, leveraging the strengths of both CLIP and StyleGAN2.
  - Cons: Increased computational complexity due to the combination of multiple models.

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4. LoRAs (Latent Optimized Reinforcement of Attributes):-

- **Approach**: Explored models like LoRAs designed for fine-grained control over image attributes by optimizing latent representations.
- **Experiments**: By manipulating latent codes corresponding to desired attributes, aimed to achieve precise control over image features.
- **Observations**: LoRAs demonstrated results in terms of steerability but required careful optimization and tuning of latent codes.
- **Limitations:** *Complexity of Implementation*: LoRA is a sophisticated model that involves the integration of Latent ODEs (Ordinary Differential Equations) into the learning process. Implementing and training LoRA requires a deep understanding of differential equations and neural network architectures, making it challenging

5.Stable Diffusion:-

Stable Diffusion v1:

- **Description:** A latent text-to-image diffusion model trained on 512x512 images from the LAION-5B database.
- **Model Architecture:** Utilizes an 860M UNet and CLIP ViT-L/14 text encoder for the diffusion model.
- **Training:** Pretrained on 256x256 images and finetuned on 512x512 images.
- **Capabilities:** Supports text-to-image generation, guided image synthesis, inpainting, and outpainting.
- **Limitations:**
  - Issues with degradation and inaccuracies in scenarios deviating from 512x512 resolution.
  - Faces and people in general may not be generated properly.

Code implementation for generating an image from prompt using Stable-Diffusion-v1-1:

```
!nvidia-smi
!pip install diffusers transformers accelerate scipy safetensors
import torch
from torch import autocast
from diffusers import StableDiffusionPipeline
#Load the Model
model_id = "CompVis/stable-diffusion-v1-1"
device = "cuda"
pipe = StableDiffusionPipeline.from_pretrained(model_id)
pipe = pipe.to(device)
#Write the prompt
prompt = "A person standing on road with Mountain in background"
with autocast("cuda"):
    image = pipe(prompt). images[0]

# Resize the image to 2048x2048 pixels
img_resized = image.resize((2048, 2048))
#Save the image
img_resized.save("Generated image2.png")

```

Output:

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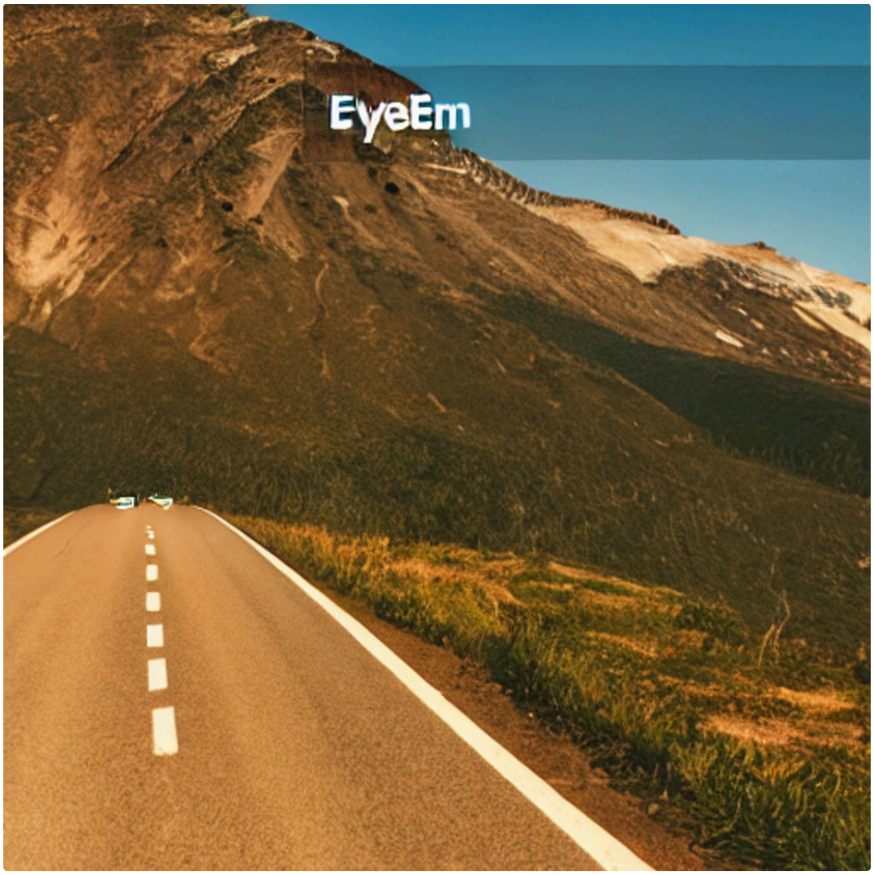

Image generated for prompt : A person standing on road with Mountain in Background

Stable Diffusion v1-4:

- **Description:** A latent text-to-image diffusion model capable of generating images based on text prompts.
- **Training Data:** Utilized the LAION-2B dataset and subsets thereof for training.
- **Training Procedure:** Combines an autoencoder with a diffusion model trained in the latent space of the autoencoder. Text prompts are encoded through a ViT-L/14 text-encoder and fed into the UNet backbone of the latent diffusion model via cross-attention.
- **Limitations**:
  - The model does not achieve perfect photorealism.
  - The model does not perform well on more difficult tasks which involve compositionality, such as rendering an image corresponding to “A red cube on top of a blue sphere”.

Code implementation for generating an image from prompt using Stable-Diffusion-v1-4:

```
!nvidia-smi
!pip install diffusers transformers accelerate scipy safetensors
from torch import autocast
from diffusers import StableDiffusionPipeline
pipe = StableDiffusionPipeline.from_pretrained("CompVis/stable-diffusion-v1-4", use_auth_token=True).to("cuda")
#Write text prompt
prompt = "A person standing on road with Mountain in background"
with autocast("cuda"):
    image = pipe(prompt).images[0]

# Resize the image to 2048x2048
image_resized = image.resize((2048, 2048))
# Save the resized image
```

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```
image_resized.save("Generated image1.png")

```

Output:

Image generated for prompt : A person standing on road with Mountain in Background

Stable Diffusion v1.5:

- **Description:** Released by Runway ML, this model is based on v1.2 with further training.
- **Capabilities:** Suitable for general-purpose image generation.
- **Benefits:** Offers higher native resolution (1024 px) compared to previous versions.
- **Limitations:**
  - The model was trained mainly with English captions and will not work as well in other languages.
  - The autoencoding part of the model is lossy.

Code implementation for generating an image from prompt using Stable-Diffusion-v1-5:

```
!nvidia-smi
!pip install diffusers transformers accelerate scipy safetensors
from diffusers import StableDiffusionPipeline
import torch
model_id = "runwayml/stable-diffusion-v1-5"
pipe = StableDiffusionPipeline.from_pretrained(model_id, torch_dtype=torch.float16)
pipe = pipe.to("cuda")
#Write the prompt
```

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```
prompt = "A person standing on road with Mountain in background"
image = pipe(prompt).images[0]

# Resize the image to 2048x2048
image_resized = image.resize((2048, 2048))

# Save the resized image
image_resized.save("Generated image4.png")

```

Output:

Image generated for prompt : A person standing on road with Mountain in Background

Stable Diffusion v2:

- **Description :** Stable Diffusion 2 is an evolution of the original Stable Diffusion model, incorporating improvements in architecture and training techniques. It leverages diffusion models, which are powerful generative models capable of modeling complex data distributions. The model is trained on large-scale datasets consisting of paired text descriptions and corresponding images to learn the relationships between textual inputs and visual representations.
- **Model Architecture:**
  - **Text Encoder**: Stable Diffusion 2 incorporates a text encoder component responsible for processing textual descriptions. This text encoder transforms textual inputs into high-dimensional representations, capturing the semantic meaning and context of the input text.
  - **Diffusion Model**: The core component of Stable Diffusion 2 is the diffusion model, which generates images conditioned on the learned latent representations from the text encoder. The diffusion model utilizes a series of diffusion steps to iteratively refine the

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generated image, progressively adding details and structure to the output.

- **Capabilities :** Stable Diffusion 2 offers several powerful capabilities for text-to-image synthesis tasks:
  - **High-Quality Image Generation**: The model can generate high-resolution, photorealistic images based on textual descriptions. It captures intricate details and textures to produce visually compelling outputs.
  - **Semantic Understanding**: By encoding textual descriptions into latent representations, the model demonstrates a strong understanding of semantic concepts and context. This allows for accurate translation of textual prompts into visually coherent images.
  - **Fine-Grained Control**: Stable Diffusion 2 provides fine-grained control over the generated images, enabling users to manipulate various attributes such as object placement, scene composition, and stylistic elements through textual inputs.
- **Limitations:**
  - **Complexity of Prompts**: The model's performance may degrade when presented with highly complex or ambiguous textual prompts. In such cases, it may struggle to accurately translate the textual descriptions into visually coherent images.

Code implementation for generating an image from prompt using Stable-Diffusion v2:

```
!nvidia-smi
!pip install diffusers transformers accelerate scipy safetensors
from diffusers import StableDiffusionPipeline, EulerDiscreteScheduler
model_id = "stabilityai/stable-diffusion-2"
# Use the Euler scheduler here instead
scheduler = EulerDiscreteScheduler.from_pretrained(model_id, subfolder="scheduler")
pipe = StableDiffusionPipeline.from_pretrained(model_id, scheduler=scheduler, torch_dtype=torch.float16)
pipe = pipe.to("cuda")
#write the prompt
prompt = "A person standing on road with Mountain in background"
image = pipe(prompt).images[0]

# Resize the image to 2048x2048
image_resized = image.resize((2048, 2048))


# Save the resized image
image.save("Generated image5.png")

```

Output:

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Image generated for prompt : A person standing on road with Mountain in Background

Stable Diffusion v2-1:

- **Description:** A fine-tuned model from stable-diffusion-2 with additional training steps on the same dataset.
- **Model Architecture:** Uses a text encoder (OpenCLIP-ViT/H) and a latent diffusion model for text-to-image generation.
- **Capabilities:** Generates and modifies images based on text prompts.
- Limitations:
  - Faces and people in general are not be generated properly.
  - The model cannot render legible text.

Code implementation for generating an image from prompt using Stable-Diffusion-2-1:

```
import torch
from diffusers import StableDiffusionPipeline, DPMSolverMultistepScheduler

model_id = "stabilityai/stable-diffusion-2-1"

# Use the DPMSolverMultistepScheduler (DPM-Solver++) scheduler here instead
pipe = StableDiffusionPipeline.from_pretrained(model_id, torch_dtype=torch.float16)
pipe.scheduler = DPMSolverMultistepScheduler.from_config(pipe.scheduler.config)
pipe = pipe.to("cuda")
prompt = "A person standing on road with Mountain in background"
image = pipe(prompt).images[0]

# Resize the image to 2048x2048
image_resized = image.resize((2048, 2048))
```

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```
15
16 # Save the resized image
17 image.save("Generated image3.png")
```

Output:

Image generated for prompt : A person standing on road with Mountain in Background

These models represent advancements in text-to-image generation, each with specific training data, architectures, capabilities and contributing to the field of AI-driven image synthesis.

 Epic realism	 Stable diffusion-v1	 Stable diffusion v1-4	 Stable diffusion-v1.5	 Stable diffusion-v2	 Stable diffusion v2-1	**Images Generated for same prompt "A person standing on road with Mountain in background"**

Conclusion:

Based on the experimentation process by considering the core requirements like:

I . Model Comparison: The document explored various AI models for image generation, including community-finetuned checkpoints, custom models, mixtures of models, LoRAs, and Stable Diffusion models. Each model demonstrated unique strengths and limitations in terms of

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photorealism, steerability, and computational efficiency.

II . Photorealism and Steerability: Models like Epic Realism and Stable Diffusion v2 exhibited exceptional photorealism, capturing intricate details and textures with remarkable fidelity. While custom models offered greater steerability, allowing fine-grained control over image details based on text prompts.

III . Resource Efficiency: Models like StyleGAN2 and Stable Diffusion v1.5 provided a balance between computational complexity and image quality, making them suitable for practical applications.

IV . Optimization and Future Directions: To further enhance the experimentation pipeline, future efforts could focus on optimizing model architectures and training procedures to achieve better results in terms of both photorealism and steerability. Additionally, exploring novel techniques such as attention mechanisms and reinforcement learning could lead to further advancements in text-to-image synthesis.

Regarding the performance of the models for text prompt to image generation can be summarized as follows, from the **least to the best** :

i . DALL-E 2 : While DALL-E 2 produced highly detailed images with impressive photorealism, its limited steerability in controlling specific details of the generated images was a significant drawback. It struggled with understanding nuanced or ambiguous textual descriptions, leading to inaccuracies or inconsistencies in the generated images.

ii . Stable Diffusion v1.4 : Despite its sophisticated architecture and training techniques, Stable Diffusion v1.4 faced challenges in achieving perfect photorealism and struggled with rendering complex scenes involving compositionality. Additionally, faces and people in general were not generated properly, limiting its applicability in certain scenarios.

iii . Stable Diffusion v1.5 : While offering higher native resolution compared to previous versions, Stable Diffusion v1.5 was mainly trained with English captions, which might affect its performance with prompts in other languages. The autoencoding part of the model was lossy, potentially impacting the fidelity of the generated images.

iv . Community-Finetuned Checkpoints (e.g.,Epic Realism): Models fine-tuned by the community, such as StyleGAN2 and Epic Realism, exhibited impressive photorealism and moderate steerability. They provided a good balance between image quality and computational efficiency, making them suitable for practical applications.

v . Stable Diffusion v2: Representing an evolution of the original Stable Diffusion model, Stable Diffusion v2 offered several powerful capabilities for text-to-image synthesis tasks. It excelled in generating high-resolution, photorealistic images while demonstrating a strong understanding of semantic concepts and context. With fine-grained control over image attributes, Stable Diffusion v2 emerged as one of the top-performing models for text prompt to image generation.

In summary, while each model demonstrated unique strengths and limitations, Stable Diffusion v2 emerged as the best-performing model overall, offering a powerful combination of photorealism, steerability, and computational efficiency.

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